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**BANK BEHAVIOR WITH ACCESS TO CREDIT RISK
TRANSFER MARKETS**

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Bank Behavior with Access to Credit Risk Transfer Markets

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Abstract:

One of the most important recent innovations in financial markets has been the development of credit derivative products that allow banks to more actively manage their credit portfolios than ever before. We analyze the effect that access to these markets has had on the lending behavior of a sample of banks, using a sample of banks that have not accessed these markets as a control group. We find that banks that adopt advanced credit risk management techniques (proxied by the issuance of at least one collateralized loan obligation) experience a permanent increase in their target loan levels of around 50%. Partial adjustment to this target, however, means that the impact on actual loan levels is spread over several years. Our findings confirm the general efficiency enhancing implications of new risk management techniques in a world with frictions suggested in the theoretical literature.

Keywords: credit risk transfer, risk management, bank lending

JEL Classifications: G21,G31

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In a Modigliani-Miller world banks need not actively risk manage their portfolios as shareholders can do so more efficiently by holding diversified portfolios. We obviously do not live in a Modigliani-Miller world and banks very actively manage their risks. Frictions in the market such as moral hazard and adverse selection problems lead banks to acquire private information about their borrowers that makes bank loans illiquid and hard to trade. The existence of private information also makes bank failure costly. Banks then have incentives to risk manage internally, and to hold liquid assets and capital buffers so that bankruptcy can be avoided. And if the banks do not perform these duties rigorously, bank regulators have the right to intervene.

In recent years a new set of financial instruments has been developed that allow banks to be more active in the management of their loan portfolios. Banks have long been able to trade loans or buy insurance to protect themselves against borrower default but the recent explosion of single name credit derivatives products such as credit default swaps, and portfolio products such as collateralized loan obligations (CLOs) have the potential to revolutionize bank lending due to the sheer size of credit risk that can be transferred off banks' balance sheets quickly and with relatively low cost.

In this paper we look at the behavior of a group of banks identified as having actively used advanced credit risk transfer (CRT) techniques. We compare them to a sample of banks that have not accessed these new markets for credit risk transfer to anything like the same extent. We are particularly interested in comparing the lending behavior of the two groups of banks as this may have efficiency implications.

Why should we expect to see different behavior from banks that have accessed this market? First, because banks that have accessed other new markets for risk management appear to behave differently. Brewer, Minton and Moser (2000) show that US banks that are "active participants" in interest rate derivatives markets experience greater growth in their loan portfolios than banks that are not. Similarly, and related to our paper, Cebenoyan and Strahan (2004) show that "active [credit risk] management" in the loan sales market allows banks to make more loans and to hold less capital than banks that are less active in loan sales. Second, Froot, Scharfstein and Stein (1993) and Froot and Stein (1998) present models in which active risk management can allow banks to aggressively expand their loan portfolios and to hold

less capital. More directly related to the current application, Wagner and Marsh (2006) provide a theoretical model in which a bank that has engaged in credit portfolio diversification activities reduces the risk premium it charges on loans and hence increases its lending (assuming it is not constrained by a lack of demand for credit from deserving borrowers).

We use an annual dataset spanning ten years and covering 900 of the world's largest banks, and fit a model in which banks partially adjust to a target level of loans determined by supply and demand factors. In addition to the standard supply-side factors such as capital and liquidity we introduce an indicator variable for a bank's use of advanced credit risk management (CRM) tools. We argue that banks that fail to fully utilize such tools are likely to encounter constraints on their lending because of excessive risk concentrations.

Many banks are constrained to lend to borrowers from relatively small geographic areas, leaving the bank potentially exposed to regional economic shocks. Other banks are constrained to lend primarily to certain business sectors, with analogous consequences. Even banks unrestricted in terms of who they lend to may find excessive concentrations arise in their loan portfolios. Banks may find that some large companies, with whom they have strong relationships, build up high levels of indebtedness. Sectoral exposures can also reach a bank's capacity when similar companies engage in synchronized borrowing. In recent years, telecoms companies around the world rapidly and simultaneously built up high levels of debt, in both loans and traded instruments, as they invested heavily in new technologies.

These concentrations mean that bank loan portfolios are often not optimally diversified. While marginal loans at competitive interest rates may be judged as prudent on a stand-alone basis, they might not be when judged in a loan portfolio context. Banks are forced to refuse these loans or to charge such high risk premiums that borrowers turn elsewhere for funding.

Historically, loans have largely remained on a bank's balance sheet until maturity or default. While markets for credit risk transfer, such as loan sales or credit insurance, have been in existence for a long time, they have played a relatively small role in

shifting risks between institutions. Recent developments in credit risk transfer markets have radically changed this environment, however. Banks can now sell exposure to some individual borrowers by buying protection in the credit default swap market. The number of traded reference entities (borrowers) in this market is still relatively small though growing through time. Large exposures to well-known and actively traded companies can be easily removed in this very liquid market. Even if a bank is exposed to borrowers without a liquid credit default swap market, portfolio credit risk transfer instruments such as collateralized loan obligations allow the securitization of loan exposures.

The market for credit default swaps, the most prevalent of the new credit risk management techniques, is an over-the-counter one. Participation in this market is thus difficult to detect, let alone measure. Given its ease of use, growth, and development of collateralization methods, it is hard to suggest that only a subset of banks has access to the market and even harder to definitively name these banks.¹ We assume that all banks in our sample have the ability to trade in this market. However, the limited number of reference entities traded in this market (particularly in its early years) means that using credit default swaps can have only limited impact on the credit risk management of a bank's loan portfolio – exposure to only a small sub-sample of a bank's credits can be sold this way and since most entities also have publicly traded debt instruments banks have long been able to buy exposure to these borrowers.

We argue that issuing a CLO is an observable signal that a bank is fully engaged in advanced credit risk management. Put another way, a bank that has not issued a CLO is unlikely to be managing credit risk to the fullest extent since it is likely to be less than optimally diversified due to excessive credit concentrations. The sheer size of CLO deals suggests their importance – the 108 CLOs in our sample have an average nominal value of almost \$900m. While the risk transferred is not necessarily closely related to the value of the deal – the first-loss equity tranche is typically retained by the bank – CLOs are probably the only way banks can shift large amounts of risk off

¹ There is evidence that, in fact, very few US banks actually use the credit derivatives market (Stulz et al, 2005). However, while evidence outside the US is limited, discussions with market participants suggest that many European banks use credit default swap markets.

their books. In the absence of CLOs, moral hazard issues may preclude the transfer of credit risk for certain classes of borrowers where lending relationships are strong. CLOs, however, allow banks to securitize such loans and find willing buyers. By shedding sub-optimal concentrations banks can reduce the risk premiums charged to all borrowers, and expand their loan book to the capacity dictated by other demand and supply factors.

We find that banks that move to adopt advanced credit risk management techniques (i.e. banks that issue a CLO) see a permanent 50% increase in their target level of loans, other things equal. Since banks only partially adjust loans to the target level the immediate impact is nearer to 20%, with the remainder of the increase in loans spread over subsequent years. To have a similar impact on the target level of loans, equity capital would have to increase by around 60%. The effect of advances in credit risk management techniques is therefore statistically and economically very significant. Our findings support the theoretical work on the implications of advances in risk management techniques, and complement empirical papers demonstrating similar, though much smaller, effects on loan levels from the active use of other risk management tools.

The rest of the paper is organized as follows. Section 1 briefly outlines developments in the collateralized loan obligation market. Section 2 details our theoretical approach and develops our estimates equation. Section 3 describes the data, and Section 4 the estimation methods. Section 5 presents the results and is followed by a short concluding section.

1. Collateralized loan obligations

A balance-sheet collateralized loan obligation is a form of securitization in which assets (bank loans) are removed from a bank's balance sheet and packaged into marketable securities that are sold on to investors.² Different tranches of the CLO

² The main alternative to a balance sheet CLO is an arbitrage CLO. In these, an asset management firm will buy credit risk in the market before selling claims on the repackaged risk. The originator of the deal profits from the yield differential between the assets in the portfolio and the cost of funding the assets through the sale of securities. Since these are not securitizations that affect a bank's balance sheet we do not include them in our analysis.

have different risk-return characteristics and can be targeted at specific investor classes. One appeal of certain CLO tranches has been that they can offer more attractive yields than similarly rated securities. Barclays Capital noted in 2003 that a triple-A rated corporate debt securitization could easily have a spread as much as three times higher than a credit card-backed securitization. Of course, corporate debt securitizations had experienced extremely high downgrade rates in the preceding years, suggesting that ratings may not be perfectly transferable across instruments.

The first significant step in the development of the CLO market was the \$5bn ROSE Funding #1 issue by the UK's National Westminster Bank in September 1996.³ This CLO was backed by an international portfolio of more than 200 commercial loans. One year later, NationsBank launched a \$4bn CLO, the first significant deal in the US. Japanese and Continental European banks soon followed. Deutsche Bank's first Core CLO was largely backed by loans to medium-sized German companies. In the absence of a CLO-type structure, selling loans made to Mittelstand companies would have been difficult because of the strong lending relationships built up by German banks with their corporate clients.

A twist on the CLO structure occurred in 1999 with Deutsche Bank's Blue Stripe synthetic CLO. In this type of deal, the loans are not transferred off balance sheet before being securitized. Instead, the bank buys credit protection (thereby insuring itself against default of the loans on its books) while the protection writer has effectively bought credit risk that can be securitized.

In economic terms there is little difference between a properly structured synthetic securitization and a true asset sale balance sheet transaction. However, for our purposes, there is an important difference. In a true sale transaction, the bank exchanges loans for cash via a special purpose vehicle that trades with the public. The loans of the bank will drop while cash holdings will rise. In a synthetic deal, the loans remain on the bank's books, albeit insured against default. There is no up-front

³ Continental Bank's FRENDS issue in 1988 is often cited as a precursor to the CLO market, but this was a relatively isolated deal. The NatWest issue started a mass movement towards loan securitization and will, for the purposes of this paper, be credited as the beginning of the CLO market.

increase in cash, and indeed the bank is committed to pay for the credit protection in installments.

2. Theoretical model and empirical framework

We assume that banks adjust the current value of their loans ($L_{i,t}$) according to a degree of adjustment coefficient, λ , to obtain a target level of loans ($L_{i,t}^*$):

$$\frac{L_{i,t}}{L_{i,t-1}} = \left(\frac{L_{i,t}^*}{L_{i,t-1}} \right)^\lambda \quad (1a)$$

or, in natural logarithms

$$l_{i,t} - l_{i,t-1} = \lambda(l_{i,t}^* - l_{i,t-1}) \quad (1b)$$

If $\lambda = 0$ no adjustments are made, possibly because the costs of adjustment outweigh the costs of remaining away from target. If $\lambda = 1$, then full adjustment is made within one time period of analysis (one year in our analysis).

The target level of loans is assumed to be a function of a set of N explanatory factors:

$$L_{i,t}^* = \prod_{n=1}^N X_{n,i,t}^{\gamma_n} \quad (2a)$$

or, in natural logarithms:

$$l_{i,t}^* = \sum_{n=1}^N \gamma_n x_{n,i,t} \quad (2b)$$

where X is a vector of N explanatory factors and γ is a vector of parameters.

Combining equations (1b) and (2b) we obtain

$$l_{i,t} = (1 - \lambda)l_{i,t-1} + \sum_{n=1}^N \lambda \gamma_n x_{n,i,t-1} \quad (3)$$

Equation (3) will form the basis of our analysis. We now turn to the specification of the explanatory variables. We begin with a brief discussion of the traditional factors used to model bank loan portfolios before focusing on the variable of particular interest, active participation in credit risk management markets.

2.1 *Traditional demand and supply factors*

Bernanke and Lown (1992) were among the first to suggest that capital requirements affect loan portfolio growth. A bank with a capital level below its desired level could seek to restore equilibrium by reducing its assets or by raising capital. Since the latter is costly, a bank might prefer to reduce its loan stock. Conversely, a bank with excess capital has the ability to expand its loan portfolios until the capital constraint begins to bind. Several measures of bank capital could in theory be considered here.

Unfortunately, the international nature of our group of banks, combined with different reporting requirements and accounting conventions, means that not all measures are available to us for a sufficiently large proportion of our sample. We are effectively constrained to just one measure, namely the total equity capital of bank i (denoted by $K_{i,t}$). If banks with a low capital to assets ratio adjust their lending to reach some target capital ratio then we would expect to see a positive relationship between a bank's equity capital and its stock of loans.

We also include bank i 's stock of liquid assets (denoted $LIQ_{i,t}$) as a determinant of its equilibrium loan level. The argument is similar to that sketched above for including the capital level. A bank that is falling short of its target liquidity level might decide to reduce its loan portfolio as part of its strategy for increasing liquidity.

As a measure of bank i 's profitability we include its return on average assets, $r_{i,t}$. Banks that are more profitable might be less constrained and less risk averse in terms of future lending. This might lead them to expand their loan portfolio compared to less profitable banks that are more reluctant to issue new loans.

These first three measures relate to the supply of loans. Demand factors are more difficult to incorporate. Previous work in modeling loan growth has typically used US data where the scope of the banks' lending books is limited by law to a small group of states. As a result, state-specific variables such as employment or real personal income could be employed as demand proxies. We take a simpler approach and include year dummies interacted with regional dummies. The regional dummies are determined by the location of the head office of the bank (Europe, Asia, Western Hemisphere or Other). The combined region-year dummies are denoted V_t (or v_t in logarithms).

2.2 *Credit risk market participation*

Even if a bank faces excess demand for loans and has the capital, liquidity and profits to support the additional loans, it may choose not to advance the loans if doing so would create risk management issues. We have in mind here a bank that has a relatively concentrated loan portfolio, perhaps because it is constrained with regard to the geographical location of its customers (e.g. the German Landesbanks) or the sectoral nature of its customers (e.g. agricultural banks). Even large and seemingly well-diversified banks may face excessive concentration in its loans to certain very large clients. While profitable to grant on a stand alone basis, further loans to these clients may be deemed too risky for the bank. If loans must remain on the books of the bank because of limited participation in credit risk transfer markets, loan portfolio concentration may be a constraint on the size of the bank's loan portfolio. However, by selling the risk attached to these loans (or by buying less correlated risk) in CRT markets the bank may be able to relax this constraint. Active participation in credit risk transfer markets is our final determinant of the size of banks' loan portfolios.

We have argued above that the best indicator of a bank's use of advanced credit risk management techniques is participation in the market for collateralized loan obligations. Depending on the structure of the transaction, a large proportion of banks' lending portfolio can be transferred off-balance sheet, and the credits in such a transaction are not limited to reference entities traded in the credit default swap market. As a result, banks can be more aggressive in their credit portfolio management using CLOs.

Our indicator of banks' participation in credit risk transfer markets is constructed as follows:

$$CLO_{i,t} = \begin{cases} 1 & \text{if bank } i \text{ issued a CLO in year } t \text{ or any previous year} \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

The dummy variable in (4) captures an 'in or out' decision to use advanced credit risk management techniques. While a bank may make only one CLO issue, it is still deemed to be active in the market for credit risk transfer since it can use many other less visible credit risk transfer instruments.

Of course, we may well be misclassifying banks using CLO issuance as our only indicator of full use of credit risk management techniques. We have argued that banks that have not issued a CLO are unlikely to be fully utilizing credit risk transfer techniques and so feel we are not under-estimating the number of banks using advanced CRM techniques. However, there may well be banks that have issued a CLO that are not in fact fully credit risk managing. Fortunately, such misclassifications will bias our results against finding an effect of CLO issuance.

Note that while we have information on the value of each CLO, we choose to use a dummy variable instead. The first reason for this is a practical one – the value of the CLO tranches sold does not necessarily tell us much about the risk that is transferred since the high-risk "toxic waste" equity tranche is usually kept by the bank (either on or off the balance sheet) making the risk transferred much less than the value of the loans transferred. Second, we are using CLO activity as an indicator for wider credit risk management activity. As such, the exact value of loans or risk transferred in the CLOs is not important. Rather, the fact that a bank is active in CLOs indicates that it is active in advanced credit risk management, and it is the impact of the latter we are trying to capture.

2.3 The estimated equation

We estimate the model with panel data. The main advantage of using panel data is to control for unobservable bank heterogeneity. In addition to the factors described above, unobservable time-invariant bank-specific factors may influence the size of a bank's loan portfolio. That is, two banks with the same levels of capital, liquid assets, and return on assets facing the same demand factors and operating to the same extent in the credit risk transfer markets might still optimally hold different amounts of loans because of unmodeled factors. To the extent that these factors are time-invariant they can be captured by firm-specific fixed effects, V_i (or v_i in logarithms).

Our model for the target level of loans is then:

$$L_{i,t}^* = K_{i,t-1}^{\gamma_1} LIQ_{i,t-1}^{\gamma_2} \left(e^{r_{i,t-1}} \right)^{\gamma_3} \left(e^{CLO_{i,t-1}} \right)^{\gamma_4} V_i V_t \quad (5a)$$

or in logarithms:

$$l_{i,t}^* = \gamma_1 k_{i,t-1} + \gamma_2 liq_{i,t-1} + \gamma_3 r_{i,t-1} + \gamma_4 CLO_{i,t-1} + v_i + v_t \quad (5b)$$

The full model to be estimated is then:

$$l_{i,t} = (1 - \lambda) l_{i,t-1} + \lambda (\gamma_1 k_{i,t-1} + \gamma_2 liq_{i,t-1} + \gamma_3 r_{i,t-1} + \gamma_4 CLO_{i,t-1} + v_i + v_t) + \lambda \varepsilon_{i,t} \quad (6)$$

where ε is a potentially serially correlated and heteroscedastic disturbance term. All the explanatory variables enter with a lag of one year. This implies that we model the target level of loans as a function of start-of-period characteristics, and assume that the bank does not revise its target during the estimation period. We test this assumption below and show that our results are invariant to this timing assumption.

The decision to use a lagged value of the *CLO* dummy is of more relevance. We justify this on two grounds. First, it ensures that the effect we measure does not interfere with the direct negative effect of balance sheet CLOs on loan growth through the removal of the underlying loans from the bank's balance sheet. Second, it ensures

that we measure the impact of CLOs on subsequent loan growth. As some CLOs are issued late in the year, it is not appropriate to use the same year's loan growth as the dependent variable.

3 Sample description and data sources

We gather data on CLOs issued by banks from the Asset Backed Alert Database. This database contains information on all rated asset-backed issues, mortgage-backed issues and collateralized bond obligations placed anywhere in the world. In addition, we collect information on the specific type of these CLOs from the Standard and Poor's 2004 report on 'Global CDO transactions rated by S&P'.

The use of CLOs can potentially impact different parts of a bank or a bank holding company. While the CLO issuing bank might be, for example, the London office of a US bank, the assets securitized might be loans to German corporate borrowers. The CLO issue could then conceivably affect the future lending decisions of the German office, the London office or the whole bank. We will assume that the size of a typical CLO issue is such that it is likely to affect the lending decisions of the bank as a whole.

In order to establish whether the CLO issuing banks in the Asset Backed Alert Database are part of a parent bank or bank holding company, we extract ownership information for each of these banks from the Bankscope database. This database contains financial information on over 13,000 banks worldwide. If a CLO issuing bank does not have another bank as a majority shareholder, we define it as independent and leave its entry unchanged. However, if a CLO issuing bank does have another bank as a majority shareholder, we collect information on when this majority share was obtained. If it was obtained before the first CLO was issued, we replace the CLO issuing bank by the majority shareholder bank. This ensures that we capture the lending decisions of the bank as a whole. If the majority share was obtained after the first CLO, we leave the entry of the CLO issuing bank unchanged.

We then extract balance sheet information for each of the banks for the years 1995 to 2004 from the Bankscope database. This leaves us with a group of 65 banks that have

issued one or more CLOs since 1995 with matching data on loans, assets, equity capital, liquid assets and returns on average equity over a ten year period. These are the group of banks we deem to have been actively using credit risk transfer techniques.

In order to extend the sample to banks that did not issue CLOs at any time during our ten-year window, we extract balance sheet information for a group of 900 banks from Bankscope. This group is selected in the following way. First, for reasons of comparison, we only select banks that do not have a majority shareholder,⁴ are of the same types as the CLO issuing banks,⁵ and are not parent banks of any of the CLO issuing banks. Second, from these banks, we select the 900 largest measured by total assets. This leaves us with a sample that includes 64 of our 65 CLO issuing banks⁶ as well as 836 banks that did not issue CLOs. The 64 CLO banks in our sample issued 161 CLOs over the period 1995-2004. Figure 1 presents a graph of the evolution of this CLO issuance. In the first three years few CLOs were issued, which might be due to the complexity of such transactions and the vast amounts involved. Between 1998 and 2002 the use of CLOs increased. Part of this acceleration can also be attributed to the introduction of the synthetic CLOs in 1999.

Our sample thus starts with 9000 bank-year observations. We lose some observations due to missing or obviously incorrect data. In addition, there are some loan growth rates substantially in excess of 100%, usually due to merger activities. These too are deleted from the sample.

Table 1 reports summary statistics for all variables used in estimation. The first column refers to the full sample. Columns 2 and 3 compare banks that issued CLOs with banks that did not. Several points stand out. First, CLO banks tend to be much

⁴ This condition is relaxed only for the CLO issuing banks that were independent at the time of the first CLO but are not anymore.

⁵ Our CLO issuing banks all belonged to one of the following types: commercial banks, bank holding and holding companies, investment banks, cooperative banks, credit banks, specialized governmental credit institutions, and savings banks.

⁶ We lose one CLO issuing bank because of its relatively small size compared to other CLO issuing banks. Extending the sample to include this bank would imply a much larger sample that would be less representative for CLO issuing banks in general. The smallest remaining CLO issuing bank is in the smallest decile (by assets or loans) of our sample of 900 banks.

larger than non-CLO banks both in terms of total loans and total assets.⁷ This might be due to the complexity of CLO transactions and the vast amounts involved. Nevertheless, loan to assets ratios of CLO and non-CLO banks are comparable. Second, CLO banks tend to hold lower equity capital as a proportion of total assets. This is likely to be related with the size difference as large banks might be better able to manage risk and therefore can afford to hold lower capital.

These differences raise the possible problem of sample selection bias. If there is unobserved heterogeneity between our sub-samples of CLO and non-CLO banks, and if this heterogeneity is relevant for banks' intermediation, our regression coefficients will be biased. As far as this heterogeneity is time invariant, our bank-specific fixed effect fully removes these concerns. But as far as the heterogeneity is time varying, the problem remains. Below we attempt to restrict our sample to minimize this heterogeneity.

4. Estimation methods

Estimating equation (6) by OLS without firm-specific effects (v_i) could give biased coefficients because the v_i terms are potentially correlated with other regressors in the model. Furthermore, since the lagged dependent variable may also be correlated with the firm-specific effects any estimates would be inconsistent. In a short panel such as ours, this effect is particularly pronounced. While it is possible to eliminate the firm-specific effects by estimating the model in first differences, OLS-based estimates would still be incorrect because $\Delta \varepsilon_{i,t}$ is correlated with $\Delta l_{i,t-1}$ due to the correlation between $\varepsilon_{i,t-1}$ and $l_{i,t-1}$. Further, while we have lagged the explanatory variables by one period there is no guarantee that they are strictly exogenous. Banks may manage their asset and liability structures over horizons of several periods suggesting that while predetermined, lagged explanatory variables are not strictly exogenous as required by OLS.

The simplest way around the correlation between the disturbance term and lagged dependent variable is to use the instrumental variables technique of Anderson and

⁷ Stulz et al (2005) find similar results for the use of credit derivatives in US banks.

Hsiao (1982). This proposes the use of $\Delta l_{i,t-2}$ or $l_{i,t-2}$ as instruments for $\Delta l_{i,t-1}$ since by construction they are correlated with $\Delta l_{i,t-1}$ but not with the contemporaneous disturbance term. This technique is not likely to be efficient, however, since it does not use all the related moment conditions and, further, relies on the disturbance terms being serially uncorrelated.

Arrelano and Bond (1991) suggest a GMM estimator that can control for all the problems faced by OLS in estimating such dynamic panel data models. The main advantage of the GMM technique is that it can exploit all of the linear moment restrictions specified by the model and employ additional instruments obtained from using the orthogonality conditions between the disturbance terms and the lagged dependent variable. Briefly, the Arrelano and Bond difference-GMM estimator treats the model as a system of equations, one for each time period. The equations differ only in their instrument sets. Endogenous and predetermined variables in first differences are instrumented with suitable lags of their own levels, while strictly exogenous variables are instrumented conventionally.

While theoretically superior to the Anderson-Hsiao approach, the difference-GMM estimator performs poorly when faced with a short sample period and relatively persistent data. In these circumstances the coefficient on the lagged dependent variable is downward-biased. Consequently, the coefficients of any explanatory variables correlated with the lagged dependent variable are also biased. The problem is that lagged levels are often poor instruments for the first differences. Arellano and Bover (1995) propose the system-GMM estimator which adds the equations in levels to the system. This increases the number of moment conditions that can be used, thereby increasing the efficiency of the estimator. In these additional equations, predetermined and endogenous variables in levels are instrumented with suitable lags of their own first differences. Blundell and Bond (1998) demonstrate that the system-GMM estimator has dramatic efficiency gains over difference-GMM, particularly in the short sample, persistent data case. The main assumption of the system-GMM estimator is that the unobserved firm-specific effects are not correlated with changes in the disturbance term. It is therefore important that the disturbance terms of the differenced equation show no sign of second-order autocorrelation. If there is no

autocorrelation in the disturbance terms then $\Delta \varepsilon_{i,t}$ should be orthogonal to the history of the variables in the model and hence variables dated $t-2$ and earlier can be used as instruments. If the disturbance term follows an MA(1) process, however, then the instrument set is restricted to variables dated $t-3$ or earlier. The validity of the instrument set is tested via Hansen's J -statistic test of over identifying restrictions that is robust to heteroscedasticity and autocorrelation. Bond (2002) is a very helpful introduction to the application of these GMM estimators.

5. Results

5.1 Exploratory regressions

Table 2 presents a set of results of applying the system-GMM estimator to variants of equation (6) for different samples of banks.⁸ In each case, the lagged CLO dummy variable is treated as strictly exogenous (this is tested below), and the instrument set begins with variables dated $t-3$ or earlier. The use of more recent lags is rejected by the Hansen tests irrespective of the regression specification except where noted below. We employ the one-step estimator although results from using the two-step estimator are very similar as discussed below. Standard errors, robust to serial correlation within groups (banks) and heteroscedasticity of an arbitrary form are reported below the coefficient estimates.

Column (1) of Table 2 reports results using the full set of 857 banks for which we have sufficient data. Adjustment to equilibrium is slow since the coefficient on the lagged dependent variable is close to, although statistically significantly below, unity. The standard explanatory variables are at best only weakly significant although we note that the CLO indicator is significant and positive. The (unreported) region-year dummies designed to capture demand-side forces are jointly highly significant in this and all subsequent regressions. More worryingly for the use of the Arellano-Bond estimator, the Hansen test of the validity of the instruments is rejected at the one-percent level.

⁸ All estimation was performed in Stata version 9 using the xtabond2 code generously provided by David Roodman.

One advantage of panel data is that it allows information from different cross-section units to be pooled. Of course, this pooling is only advantageous if the different cross-section units are homogeneous. Pooling heterogeneous units is a possible reason for the poor results in column (1). In particular, it might not be valid to include the smallest banks in our sample alongside the largest. Column (2) omits the bottom 30% of banks in each year from the original sample as measured by the size of the loan book. Since the smallest CLO-issuing bank is much smaller than all the others, this only removes one CLO-issuing bank from the analysis. This reduction proves to be an important one, although by itself, this change is insufficient to eradicate the problems with the instruments. It also induces second order serial correlation. Nevertheless, the estimates are not far from our preferred specifications discussed below. In particular, we note that the adjustment speed is higher and most of the explanatory variables are correctly signed and significant.

In an attempt to remove the second order serial correlation problems we introduce contemporaneous regressors in column (3). Only one of these is significant and so in column (4) all the other contemporaneous explanatory variables are dropped. This specification passes all the necessary diagnostic tests and all the explanatory variables are significant and take their expected signs. The coefficients on contemporaneous and lagged liquid assets suggest that the *change* in liquid assets is important in determining the equilibrium level of loans.⁹ The inclusion of this term is particularly important for removing the second order serial correlation problem.

The lagged CLO dummy is positive and significant at the one-percent level. Banks that have issued a CLO and are therefore deemed to be actively managing their credit risk see a significant increase in the target value of their loan portfolios. The magnitude of the impact is surprisingly high. The estimated coefficients in column (4) suggest that active credit risk management increases the target loan level by 75% (computed as $\exp[\gamma_4/(1-\lambda)]-1$ from equation (6)).

5.2 Main findings

⁹ Because of the potentially high correlation between contemporaneous (though instrumented) change in liquid assets and the change in loans, we replace the former with the lagged change in liquid assets. The results (not reported) are essentially unchanged. We continue with the contemporaneous change since this gives us one extra year in the sample.

In Table 3 we attempt to refine these results. Columns (5) and (6) examine further the possible heterogeneity of our sample. Banks in our sample are primarily commercial banks or bank holding companies (BHC) that include commercial bank operations. However there are just over one hundred banks falling into other categories including investment banks, co-operative banks, and government-owned banks. In columns (5) and (6) we report the results using just the sample of commercial/BHC banks and ‘other’ banks respectively. The results suggest that these two groups behave differently and should not be pooled together. In particular, the ‘other’ banks respond much less to equity capital and slightly more to liquidity than commercial/BHC banks. They also close the gap between actual and target loans much more slowly.

Column (5) is our preferred specification.¹⁰ The explanatory variables for the target level of loans for commercial/BHC banks are correctly signed and statistically significant at the usual levels of confidence. Importantly, given the adjustment speed of 42.3%p.a., the magnitude of the coefficient on the CLO indicator variable suggests that the adoption of advanced credit risk management techniques increases the target level of loans by a statistically and economically significant 50%. Given the other parameter estimates in column (5), this is equivalent to increasing the equity capital of the bank by some 60%. This suggests that the credit risk constraints on loans have been very important for commercial banks in the recent past, and that the easing of these constraints through developments in credit risk management tools has been substantial.

Column (7) reports the results of the asymptotically more efficient two-step estimator with the Windmeijer (2005) finite-sample correction to the covariance-matrix.¹¹ The results are broadly comparable with those in column (5). Most importantly for the specific issue of this paper, while the speed of adjustment is reduced this is offset by the lower coefficient on the CLO dummy leaving the impact of the adoption of credit risk management techniques on target loan levels unaffected at 50%.

¹⁰ In this regression specification, both loans and liquid assets are treated as endogenous variables with observations dated $t-3$ or before used as instruments. The return on assets and equity capital are treated as predetermined variables with observations dated $t-2$ or before used as instruments.

¹¹ In the absence of this correction the standard errors from the two-step estimator are severely downward biased.

We next examine the degree of exogeneity of the CLO dummy variable. Column (8) treats the lagged CLO indicator as a predetermined variable (to date it has been treated as strongly exogenous). The results are essentially unchanged from those in column (5) and comparison of the Hansen tests statistics across the two regressions suggests that the indicator can legitimately be treated as exogenous.

5.3 Robustness

In this section we examine whether our interpretation of CLO-issuance capturing an ‘in or out’ decision to fully adopt advanced credit risk management techniques is appropriate. Table 4 reports the key parameter estimates from augmenting model (5), our preferred specification, with additional variables designed to test this hypothesis. In column (1) we add a CLO count variable to the regression. This variable equals the cumulated number of CLOs issued by the bank and should reveal whether each successive CLO issuance has an impact on the loan decisions of the bank. The coefficient estimate is insignificantly different from zero, while the coefficient on the basic CLO dummy remains almost unaffected. Column (2) tests whether issuance of a second CLO has an impact on the target level of loans over and above the effect of the first CLO issue. Again, the new variable is insignificant. Finally, column (3) reports the results of including a dummy variable that takes a value of unity only in the year the first CLO is issued. This specification tests whether the short-term (one year) impact of the first CLO issue is different from its long-term impact. A negative value for this ‘temporary’ dummy variable would suggest that the bank does not feel the full effect on its target level of loans within the year but that it builds up over time.¹² The long-term impact would be given by the standard CLO dummy. Conversely, a positive coefficient on the temporary dummy would suggest short-term overshooting of the long-term level. The temporary dummy, though negative, is statistically insignificant.

As a whole, these results suggest that the first CLO is the only truly important one, consistent with our hypothesis that CLO issuance represents a transition from not meaningfully using credit risk management techniques to fully adopting them. The effect of this transition on target loan levels is felt quickly.

¹² Note that, because of the partial adjustment nature of the model, the effect of a permanent and immediate jump in the target loan level on the *actual* level of loans is only gradually felt through time.

5.4 *Reverse causality*

Although our preferred regression appears well specified the suspicion remains that our results are influenced by reverse causality. That is, instead of the decision to issue a CLO leading subsequently to an increase in loan supply, banks may decide to raise loan supply and accommodate this through a CLO issuance. Because of long-horizon strategic planning by banks the temporal ordering of the CLO issuance and loan growth are not sufficient to identify the direction of causality.¹³ In this sub-section we attempt to address this concern by splitting our sample of CLO issuing banks into those more and less likely to be subject to reverse causality.

We have argued that CLO issuance is capturing the adoption of advanced credit risk management techniques by a bank. This improvement in risk management allows the bank to increase its target level of loans. The banks most likely to be issuing a CLO for risk management reasons are those with the highest franchise value to protect (Demsetz et al, 1996). Banks with low franchise values, conversely, are more likely to be issuing a CLO not for risk management reasons, but instead as a tool for growing their loan portfolio (perhaps even gambling for redemption). We use the market to book ratio at the time of first CLO issuance as our indicator of franchise value. We split the CLO-issuing banks into two groups where a high ratio (greater than the median) is an indicator of high franchise value and a value below the median is an indicator of low franchise value.¹⁴ We allow the coefficient on the CLO indicator to differ for high and low franchise value groups, but constrain all other coefficients to be equal.

The estimates of the two CLO coefficients are very close to one another and are certainly not statistically distinguishable.¹⁵ We interpret this as suggesting that reverse causality is not an issue in our regressions. It is known that participation in

¹³ That is, a bank may simultaneously decide to boost target loans and accommodate this via a CLO (reverse causality). Since it cannot instantaneously raise actual loans, the CLO may be issued before the loan growth materializes. The use of lagged CLO issuance in our regressions partly mitigates this risk (especially when combined with the length of time needed to structure a bank's first CLO).

¹⁴ This is the best measure of franchise value that can be computed from our international database since variables such as goodwill used in more sophisticated measures are not available.

¹⁵ The two coefficients are 0.179 (low franchise value) and 0.163 (high franchise value). The p-value of a test of coefficient equality is 0.765.

credit derivatives markets is limited to a small number of large, reputable banks (Ashraf et al, 2006; Minton et al, 2005). Though some may have more franchise value than others, banks in both groups are likely to have franchise value to protect and are therefore likely to be issuing CLOs as part of their risk management strategy.¹⁶

6. Conclusions

In this paper we have explored the implications of developments in credit risk transfer markets on banks' lending behavior. We identify banks that have issued at least one collateralized loan agreement as fully utilizing advanced credit risk management techniques. Since these securities are arguably the only way a bank can remove large amounts of credit risk from a wide enough range of borrowers, we argue that banks that have not issued a CLO are unlikely to be managing credit risk to the fullest extent possible.

Our model assumes that banks have a target level of loans that they would like to issue that is determined by supply and demand factors. In addition to standard supply-side determinants such as available capital and liquidity, we argue that risk limits may be binding due to high geographic/sectoral concentrations in the loan book or excessive exposure to small numbers of individual borrowers. To the extent that developments in credit risk transfer techniques, and in particular CLO issuance, have relaxed this constraint, adopting advanced credit risk management tools will allow banks to increase their target levels of loans.

We test this model empirically in a dynamic panel data framework. Our econometric techniques are robust to the possible endogeneity of the determinants of target loan levels and are capable of capturing slow adjustment to target levels. The explanatory variables are statistically significant and correctly signed. More importantly, we find that banks that adopt advanced credit risk management techniques (proxied by the issuance of at least one CLO) experience a permanent increase in their target loan levels of around 50%. Partial adjustment to this target, however, means that the

¹⁶ The mean and median market to book ratio for our sample of CLO issuing banks are both close to two, and only two banks had a market to book ratio below unity at time of CLO issuance.

impact on actual loan levels is spread over several years. Our findings confirm the general efficiency enhancing implications of new risk management techniques in a world with frictions suggested in the theoretical literature, and complement empirical findings of positive impacts on loan growth from other risk management advances.

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Figure 1: Number of CLOs issued 1995-2004

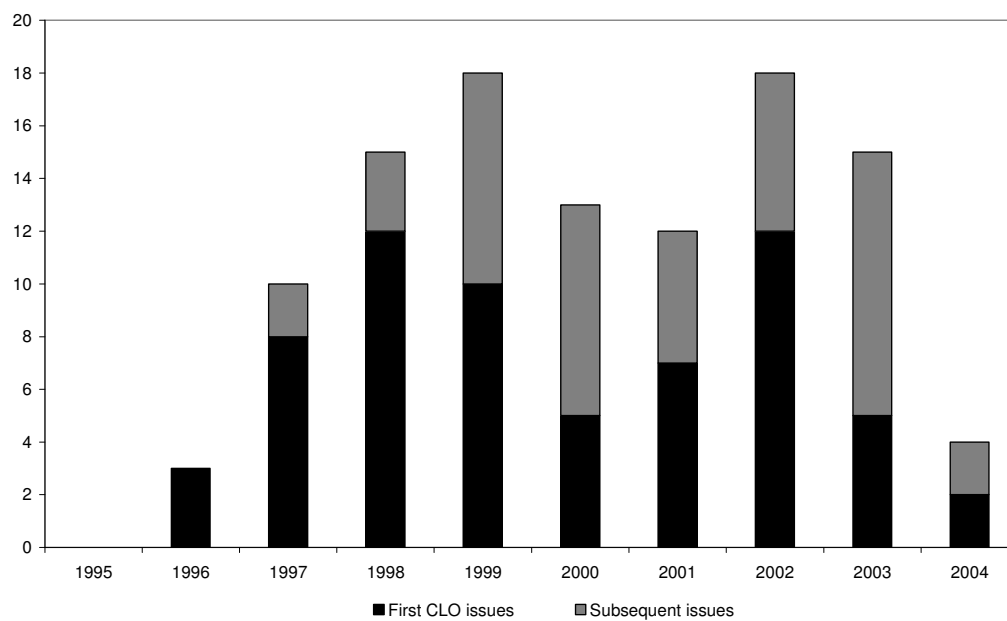


Table 1: Summary statistics for key variables

Variables	All banks		CLO banks		Non-CLO banks	
	Mean	Std dev	Mean	Std dev	Mean	Std dev
Total assets (US\$ bn)	42.475	118.575	303.888	277.808	21.676	56.398
Loans (US\$ bn)	20.783	55.657	145.418	130.733	11.118	26.782
Equity capital (US\$ bn)	2.346	6.155	14.853	15.143	1.347	3.023
Liquid assets (US\$ bn)	9.826	37.715	73.772	108.307	4.737	15.900
Return on average assets (%)	0.915	2.416	0.554	0.716	0.944	2.499
Loans/Total assets	0.560	0.201	0.524	0.168	0.562	0.203
Equity capital/Total assets	0.095	0.103	0.054	0.022	0.098	0.106
Liquid assets/Total assets	0.213	0.188	0.215	0.118	0.213	0.192

Table 2

This table reports the results of estimating equation (6) in the text using the one-step version of the system-GMM estimator. Endogenous and predetermined variables dated $t-3$ and earlier enter the instrument set. CLO_{t-1} is treated as an exogenous variable. All columns include unreported region-year dummies. Robust standard errors are reported in parentheses below the parameter estimates. The row denoted ‘Hansen test’ reports Hansen’s J test statistic of the over-identifying restrictions. Degrees of freedom are reported in parentheses below. Rows denoted A-B AR(x) give the test statistic of Arellano and Bond’s test for autocorrelation of order x . ***, **, and * denote significance at the 1%, 5% and 10% level respectively. Column (1) uses the full data sample available. Column (2) excludes the smallest 30% of banks by loans each year. Column (3) augments equation (6) with contemporaneous regressors and excludes the smallest 30% of banks by loans each year. Column (4) augments equation (6) with the contemporaneous (log) level of liquid assets and excludes the smallest 30% of banks by loans each year.

	(1)	(2)	(3)	(4)
$\ln(\text{loans})_{t-1}$	0.8893*** (0.0577)	0.6743*** (0.1068)	0.6356*** (0.1282)	0.6580*** (0.1104)
$\ln(\text{equity capital})_t$			0.2032* (0.1232)	
$\ln(\text{equity capital})_{t-1}$	0.1011 (0.0694)	0.2708** (0.1276)	0.0895 (0.1728)	0.2344* (0.1288)
$\ln(\text{liquid assets})_t$			0.1254** (0.0595)	0.1576** (0.0719)
$\ln(\text{liquid assets})_{t-1}$	-0.0295 (0.0316)	-0.0196 (0.0446)	-0.1423** (0.0648)	-0.1533** (0.0669)
roaa_t			-0.0132 (0.0470)	
roaa_{t-1}	0.0192* (0.0114)	0.0455** (0.0186)	0.0422** (0.0199)	0.0410** (0.0174)
CLO_{t-1}	0.1400** (0.0574)	0.2027*** (0.0711)	0.1727** (0.0752)	0.1915*** (0.0714)
Observations	4859	3430	3424	3429
Number of banks	857	654	654	654
Number of CLO banks	61	60	60	60
Hansen test (degrees of freedom)	221.57*** (154)	181.80** (151)	134.69 (121)	132.29 (123)
A-B AR(1) test	-7.83***	-7.57***	-4.48***	-7.46***
A-B AR(2) test	-1.23	-2.62***	-1.65*	-1.37

Table 3

This table reports the results the results of estimating equation (6) in the text using the one-step version of the system-GMM estimator, unless otherwise noted. Endogenous variables dated $t-3$ and earlier and predetermined variables dated $t-2$ and earlier enter the instrument set. CLO_{t-1} is treated as an exogenous variable unless otherwise noted. All columns include unreported region-year dummies. Robust standard errors are reported in parentheses below the parameter estimates. The row denoted ‘Hansen test’ reports Hansen’s J test statistic of the over-identifying restrictions. Degrees of freedom are reported in parentheses below. Rows denoted A-B AR(x) give the test statistic of Arellano and Bond’s test for autocorrelation of order x . ***, **, and * denote significance at the 1%, 5% and 10% level respectively. Column (5) uses only commercial and BHC banks excludes the smallest 30% of banks by loans each year. Column (6) uses only non-commercial and non-BHC banks and excludes the smallest 30% of banks by loans each year. Column (7) reports the two-step estimator of column (5) with Windmeijer’s correction to the covariance matrix. Column (8) re-estimates column (5) treating CLO_{t-1} as a predetermined variable.

	(5)	(6)	(7)	(8)
$\ln(\text{loans})_{t-1}$	0.5771*** (0.1267)	0.8964*** (0.0304)	0.6475*** (0.1155)	0.5867*** (0.1278)
$\ln(\text{equity capital})_{t-1}$	0.3509** (0.1482)	0.0539* (0.0214)	0.2548** (0.1229)	0.3437** (0.1454)
$\ln(\text{liquid assets})_t$	0.1434* (0.0731)	0.1784*** (0.0332)	0.1540** (0.0642)	0.1310** (0.0640)
$\ln(\text{liquid assets})_{t-1}$	-0.1524* (0.0819)	-0.1388*** (0.0340)	-0.1366* (0.0752)	-0.1352* (0.0727)
roaa_{t-1}	0.0244* (0.0134)	0.0291** (0.0148)	0.0197 (0.0132)	0.0255* (0.0134)
CLO_{t-1}	0.1719*** (0.0633)	0.0327 (0.0247)	0.1455*** (0.0576)	0.2020*** (0.0675)
Observations	2855	574	2855	2855
Number of banks	537	117	537	537
Number of CLO banks	45	15	45	45
Hansen test (degrees of freedom)	147.78 (140)	76.52 (114)	147.78 (140)	178.39 (175)
A-B AR(1) test	-7.37***	-4.17***	-5.17***	-7.43***
A-B AR(2) test	-1.32	-1.18	-1.10	-1.53

Table 4

This table reports selected coefficients from estimates of the specification in column (5) of Table 3 augmented with additional (exogenous) regressors as noted in the text. All columns include unreported region-year dummies. ***, **, and * denote significance at the 1%, 5% and 10% level respectively.

	(1)	(2)	(3)
$\ln(\text{loans})_{t-1}$	0.5753*** (0.1266)	0.5772*** (0.1267)	0.5788*** (0.1266)
CLO_{t-1}	0.1888*** (0.0620)	0.1697*** (0.0578)	0.1825** (0.0706)
$CLOCount_{t-1}$	-0.0086 (0.0105)		
$CLOAdditional_{t-1}$		-0.0029 (0.0409)	
$CLOFirst_{t-1}$			-0.0345 (0.0355)